

Dynamic Emissivity Estimates to Support Physical Precipitation Retrievals for GPM (Lindal)

Yalei You¹, Yudong Tian^{1,2}, Christa Peters-Lidard², Sarah Ringerud² and Joe Munchak² ¹Earth System Science Interdisciplinary Center, University of Maryland ²NASA, Goddard Space Flight Center

1. Background

- emissivity is critical of the microwave for based importance precipitation retrieval algorithm development.
- surface highly emissivity heterogeneous and dynamic, makes it difficult to estimate using physical model
- We have developed a statistical framework to estimate land surface emissivity directly from brightness temperature (TBs)
- This method is successfully applied to Southern Great Plains (SGP) by Tian et. al. (2015), which outperforms the physical model and hybrid of physical and statistical model
- We now extend this frame work to the GPMcovered region (65S-65N)

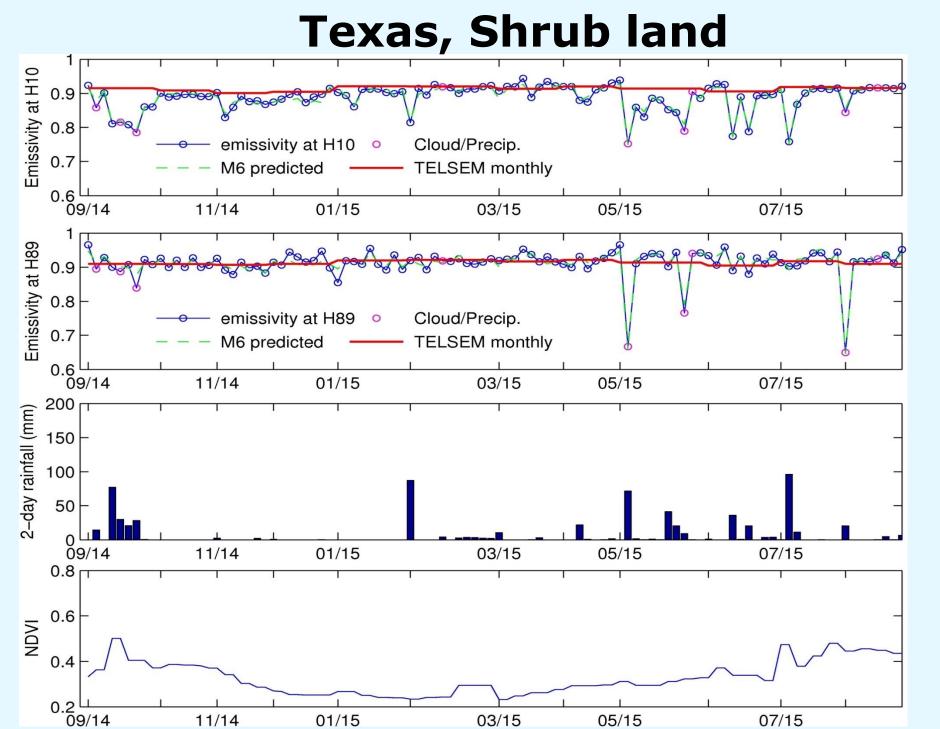
3. Datasets

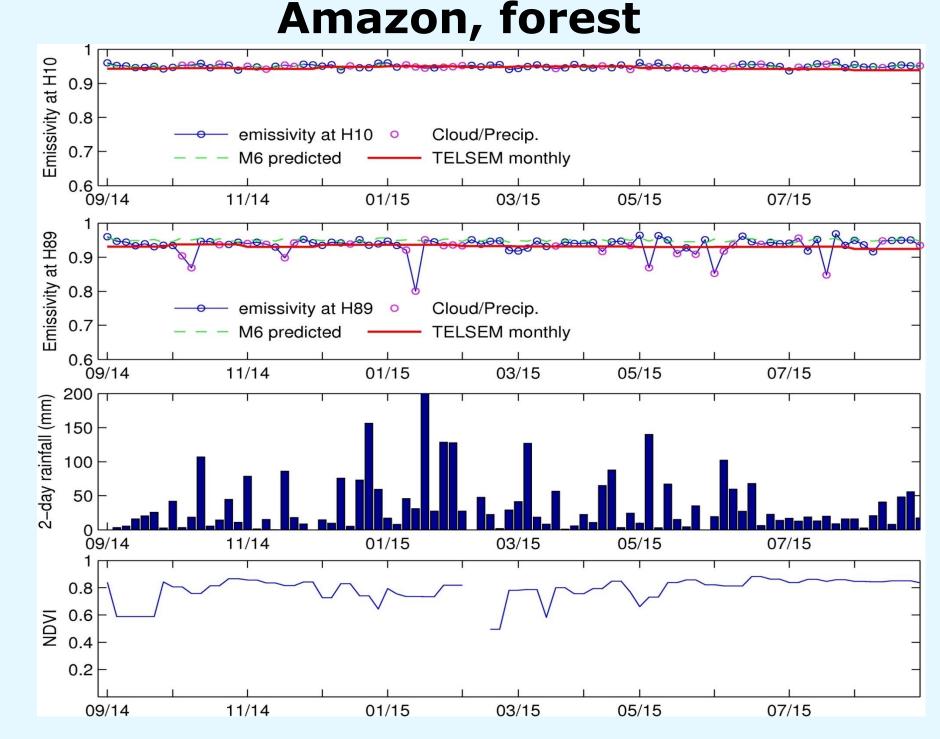
- Emissivity retrieved from GMI observed Tbs via radiative transfer model (Joe Munchack).
- GMI TBs (V10, H10, V19, ..., V166, and H166)
- IMERG 30-minute precipitation data
- TELSEM climatology (Monthly) emissivity
- MODIS Normalized Difference Vegetation Index (NDVI) (8-day and 250-meter)
- Temporal coverage: 09/2014 to 08/2015
- Spatial coverage: 65S-65N

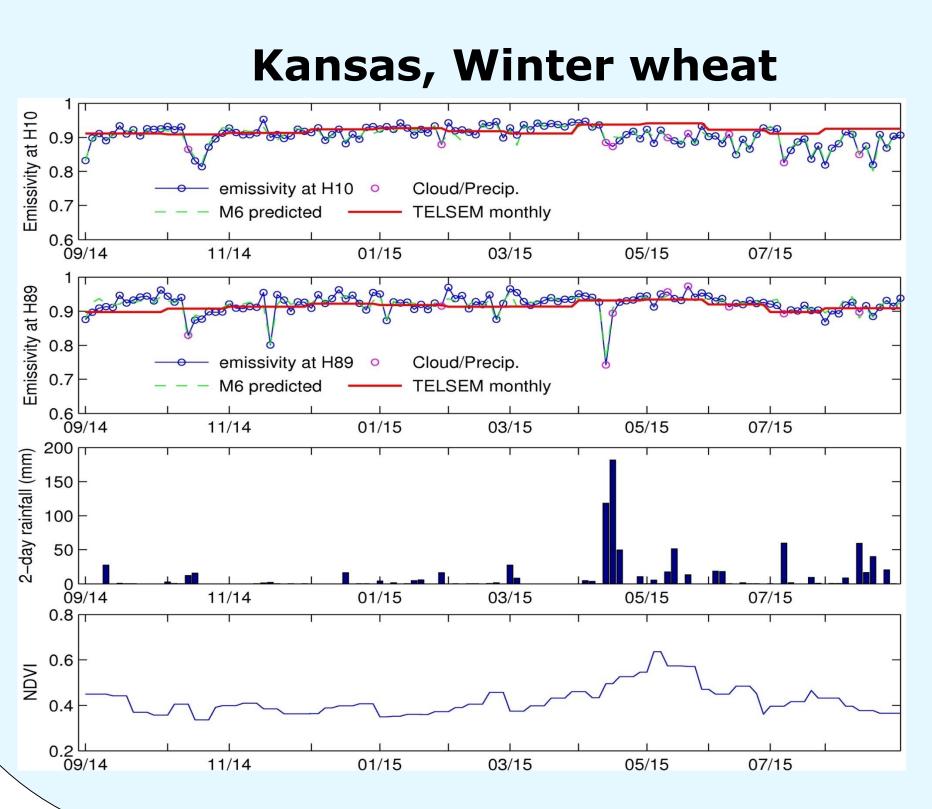
2. Methodology

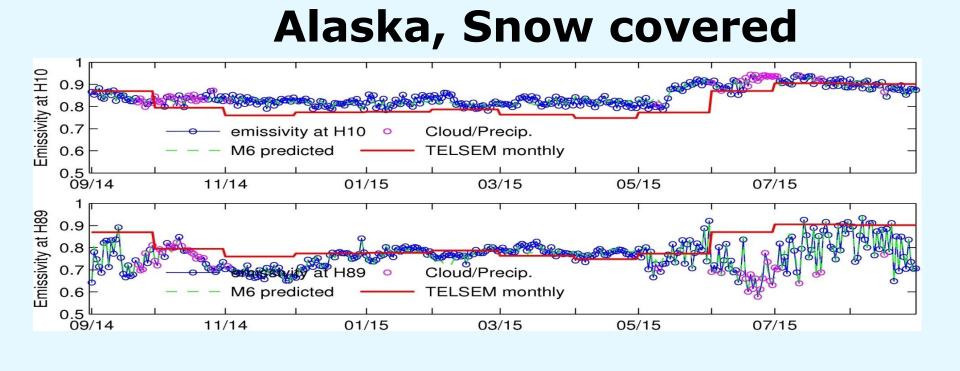
- Emissivity from 10 to 166 GHz is regressed directly from TB-based predictors
- Predictors include: TB, TB², and Microwave Polarization Difference Index (MPDI, e.g., (V10-H10)/(V10+H10))
- We have tested six different regression models
- Method 1 (M1): single channel MPDI (10 GHz) and its square (2-predictor)
- Method 2 (M2): 4-channel MPDI (10, 19, 37, and 89G), linear terms only (4predictor)
- Method 3 (M3): 9-channel TBs: 10~89 GHz, linear terms only (9-predictor)
- Method 4 (M4): 9-channel TB and 4channel MPDI, linear terms only (13predictor)
- Method 5 (M5): 9-channel TB, 9-channel TB2, and 4-channel MPDI (22-predictor)
- Method 6 (M6): 11-channel TB, 11-channel TB2, and 5-channel MPDI (27-predictor)
- Data are randomly divided into two sub-sets. one for training and the other one for validation.

4. Cases over different regions









- Many factors can lead to a large emissivity variation, including precipitation, irrigation, snow melting
- Under all conditions, our method performs very well; able to capture the dynamical change of the emissivity
- Over the Amazon forest region, a constant emissivity estimate is sufficient

5. Emissivity error estimates

Error estimates (M6) Error table Error estimates (M1) 1.30 0.90 0.87 0.99 0.97 H10 0.84 0.82 0.91 1.32 1.40 0.96 0.93 1.05 1.03 0.89 0.90 0.86 0.96 0.97 V24 1.42 0.94 1.05 V37 1.88 0.98 0.86 1.07 H37 2.46 1.81 0.94 0.91 1.02 2.83 1.20 1.16 1.26 1.23 1.39 3.82 H166 4.65 3.10 3.65 3.12

- In general, more predictors produce lower errors. Over-fitting may be an issue due to the sample size
- Emissivity estimated by 10GHz TB for all channels from 10 to 166 GHz is very accurate over the forest region (e.g., Amazon)
- High-latitude (cold surface) is less accurate

Conclusions:

- surface emissivity estimation method is extended to the GPM-covered region
- method captures dynamic the emissivity characteristics heterogeneous various regions, with average error of 0.97% to 2.80%
- The parameters in this method are directly derived from TBs without any ad hoc tuning, making it ideal for real-time application
- Future work seeks to: use cloud/precipitation screening method; (2) data for training and validation; (3) investigate the estimation over different seasons; test the dynamic emissivity in the GPM radiometer retrieval algorithm

Reference: Tian, Y., C. D. Peters-Lidard, K. W. Harrison, Y. You, S. Ringerud, S. Kumar, and F. J. Turk (2015), An examination of methods for estimating land surface microwave emissivity, J. Geophys. Res. Atmos., 120, 11,114–11,128.